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Article

# An Efficient Hybrid Machine Learning Framework For Early Skin Cancer Detection Using Deep Learning And Anomaly Detection

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**Abstract:** Skin cancer remains one of the most common and life-threatening malignancies worldwide, where early diagnosis plays a crucial role in improving patient survival. Recent advances in artificial intelligence have enabled the development of automated computer-aided diagnostic systems for accurate skin lesion analysis. This study proposes a hybrid deep learning framework for the early detection of skin cancer using dermoscopic images. The framework integrates image preprocessing, lesion segmentation, feature extraction, deep learning-based classification, and anomaly detection into a unified diagnostic pipeline. Experiments were conducted using the ISIC 2020 benchmark dataset, incorporating image enhancement, hair removal, normalization, and lesion segmentation prior to model training. A Convolutional Neural Network (CNN) was employed as the primary classification model, while Isolation Forest was utilized to identify abnormal lesion patterns and improve diagnostic robustness. The proposed framework was evaluated using accuracy, precision, recall, F1-score, Area Under the ROC Curve (AUC), confusion matrix analysis, and anomaly detection performance. Experimental results demonstrated that the proposed framework achieved superior diagnostic performance compared with conventional machine learning approaches, with the CNN providing the highest classification accuracy and the anomaly detection module enhancing the identification of difficult lesion cases. The findings demonstrate that integrating deep learning with anomaly detection provides a reliable and clinically relevant approach for early skin cancer diagnosis and offers significant potential for assisting dermatologists in computer-aided clinical decision-making.
**Keywords:** Skin Cancer Detection, Deep Learning, Convolutional Neural Network, Dermoscopic Images, Hybrid Machine Learning, Anomaly Detection, Artificial Intelligence, Computer-Aided Diagnosis.

## 1. Introduction

### *1.1 Background*

Skin cancer is one of the most prevalent and life-threatening cancers worldwide, with melanoma representing the most aggressive form because of its high metastatic potential. Early diagnosis is critical for improving treatment outcomes, reducing mortality, and increasing patient survival rates. Conventional diagnostic approaches, including visual inspection, dermoscopy, and histopathological examination, rely heavily on the expertise of dermatologists and are often associated with inter-observer variability and delayed diagnosis, particularly in regions with limited access to specialist care.

Recent advances in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have significantly transformed medical image analysis by enabling automated and highly accurate detection of skin lesions. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated excellent performance in identifying malignant skin lesions from dermoscopic images and have shown diagnostic accuracy comparable to experienced dermatologists. The availability of large public benchmark datasets, including **HAM10000**, **ISIC 2019**, **ISIC 2020**, and the more recent **ISIC 2024** challenge datasets, has accelerated the development and evaluation of robust computer-aided diagnostic systems. These datasets provide diverse and high-quality dermoscopic images that facilitate the training, validation, and benchmarking of intelligent skin cancer detection models.

Despite these advancements, achieving robust and clinically reliable skin cancer diagnosis remains challenging because of variations in lesion appearance, illumination conditions, skin pigmentation, imaging devices, and class imbalance. Therefore, there is a growing need for intelligent diagnostic frameworks that combine accurate lesion classification with mechanisms capable of identifying atypical or previously unseen lesion patterns to improve diagnostic reliability in real-world clinical environments.

### *1.2 Problem Statement*

Although numerous deep learning models have been proposed for automated skin cancer diagnosis, most existing studies focus primarily on lesion classification using a single learning paradigm. Limited attention has been given to integrating anomaly detection techniques that can identify rare or abnormal lesion patterns and improve the robustness of diagnostic systems. Furthermore, many existing studies are evaluated on a single benchmark dataset without demonstrating the generalization capability of the proposed framework across recent benchmark datasets such as ISIC 2020 and ISIC 2024. These limitations reduce the reliability and clinical applicability of current computer-aided skin cancer diagnosis systems. Therefore, there is a need for a robust hybrid framework that combines deep learning-based classification with anomaly detection to improve diagnostic accuracy, reliability, and early detection performance.

### *1.3 Research Objectives*

The primary aim of this study is to develop an efficient hybrid deep learning framework for the early detection of skin cancer using dermoscopic images. The specific objectives are:

• To review recent artificial intelligence and deep learning approaches for skin cancer detection.

• To develop an efficient skin cancer detection framework incorporating image preprocessing, lesion segmentation, feature extraction, deep learning-based classification, and anomaly detection.

• To implement and evaluate Convolutional Neural Network (CNN) and anomaly detection models using benchmark dermoscopic image datasets.

• To compare the performance of the proposed framework with existing state-of-the-art skin cancer detection methods using standard evaluation metrics.

### *1.4 Contributions of the Study*

The present study proposes a robust hybrid deep learning framework for intelligent skin cancer diagnosis. The framework integrates advanced image preprocessing, accurate lesion segmentation, deep feature learning using Convolutional Neural Networks, and anomaly detection to improve diagnostic robustness and early identification of malignant lesions. The proposed framework is evaluated using benchmark dermoscopic image datasets and multiple performance metrics to demonstrate its effectiveness. By combining deep learning with anomaly detection, the proposed approach provides a more reliable and clinically applicable computer-aided diagnostic system for early skin cancer detection.

### *1.5 Organization of the Paper*

The remainder of this paper is organized as follows. Section 2 presents the literature review and discusses recent advances in artificial intelligence and deep learning techniques for skin cancer detection. Section 3 describes the proposed methodology, including dataset description, image preprocessing, lesion segmentation, feature extraction, deep learning model development, anomaly detection, and performance evaluation. Section 4 presents the experimental results and comparative performance analysis. Section 5 discusses the findings, clinical implications, and limitations of the proposed framework. Finally, Section 6 concludes the study and outlines future research directions.

## 2. Literature Review

### *2.1 Machine Learning for Skin Cancer Detection*

Artificial intelligence has significantly advanced the field of automated skin cancer diagnosis by enabling accurate analysis of dermoscopic images. Early machine learning approaches relied on handcrafted features such as colour, texture, border irregularity, and shape descriptors extracted from segmented lesions. These features were subsequently classified using algorithms including Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbour (KNN), and Logistic Regression. Although these techniques demonstrated satisfactory performance for binary classification, their effectiveness depended heavily on feature engineering and image quality. Moreover, handcrafted feature extraction often failed to capture the complex visual characteristics of malignant skin lesions, thereby limiting diagnostic accuracy.

### *2.2 Convolutional Neural Networks for Skin Cancer Detection*

The introduction of Convolutional Neural Networks (CNNs) has transformed automated skin cancer diagnosis by enabling end-to-end feature learning directly from dermoscopic images. CNN architectures such as VGGNet, ResNet, DenseNet, EfficientNet, MobileNet, and Inception have demonstrated excellent performance in lesion classification without requiring manual feature extraction. Recent studies have reported classification accuracies exceeding 90% on benchmark datasets such as HAM10000, ISIC 2019, and ISIC 2020. CNNs effectively learn hierarchical image representations and have achieved diagnostic performance comparable to experienced dermatologists. However, CNN models may experience reduced performance when faced with highly imbalanced datasets, rare lesion categories, or images acquired under different clinical conditions.

### *2.3 Vision Transformers in Medical Image Analysis*

Vision Transformers (ViTs) have recently emerged as an alternative to conventional convolutional neural networks for medical image classification. Unlike CNNs, Vision Transformers employ self-attention mechanisms to model long-range dependencies within images, enabling more effective global feature representation. Several recent studies have demonstrated that ViT-based architectures achieve competitive or superior performance compared with CNNs for skin lesion classification, particularly when trained using large-scale datasets. Nevertheless, Vision Transformers generally require substantially larger training datasets and higher computational resources, which currently limits their widespread adoption in routine clinical applications.

### *2.4 Explainable Artificial Intelligence for Skin Cancer Diagnosis*

Although deep learning models provide high diagnostic accuracy, their decision-making processes often remain difficult to interpret. Explainable Artificial Intelligence (XAI) has therefore become an important research direction in medical imaging. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM), SHapley Additive exPlanations (SHAP), and Local Interpretable Model-Agnostic Explanations (LIME) enable visualization of image regions influencing model predictions. These approaches improve model transparency, increase clinician confidence, and support regulatory acceptance of AI-assisted diagnostic systems. Despite recent progress, explainability techniques remain absent from many existing skin cancer detection frameworks.

### *2.5 Hybrid Deep Learning Models*

Recent research has increasingly focused on hybrid diagnostic frameworks that combine multiple artificial intelligence techniques to improve classification accuracy and robustness. Hybrid approaches integrate deep feature extraction with traditional machine learning classifiers, ensemble learning methods, attention mechanisms, and feature fusion strategies. Such frameworks have demonstrated improved generalization capability by exploiting complementary strengths of different algorithms. However, many existing hybrid systems concentrate primarily on classification performance while providing limited mechanisms for identifying rare or abnormal lesion patterns that may occur in real clinical environments.

### *2.6 Anomaly Detection in Medical Imaging*

Anomaly detection has emerged as an important component of intelligent medical diagnostic systems because it enables identification of unusual or previously unseen disease patterns. Algorithms such as Isolation Forest, One-Class Support Vector Machine (One-Class SVM), and Autoencoder-based anomaly detection have been successfully applied to identify abnormal medical images without relying entirely on labelled training data. In skin cancer diagnosis, anomaly detection provides an additional safety mechanism by identifying suspicious lesions that may not closely resemble the training examples. Consequently, integrating anomaly detection with deep learning classification can improve diagnostic robustness and reduce the likelihood of missed malignant cases.

### *2.7 Summary of Existing Literature*

The existing literature demonstrates remarkable progress in automated skin cancer diagnosis through machine learning and deep learning techniques. CNN-based models remain the dominant approach because of their excellent feature learning capability, while Vision Transformers and Explainable Artificial Intelligence have emerged as promising research directions. Hybrid learning frameworks have further improved classification performance by combining multiple learning strategies. However, most existing studies continue to emphasize classification accuracy alone and rarely incorporate anomaly detection mechanisms capable of identifying unusual lesion patterns. Furthermore, only a limited number of studies evaluate their proposed frameworks using recent benchmark datasets such as ISIC 2020 and ISIC 2024, highlighting the need for more robust and clinically reliable diagnostic systems.

### *2.8 Research Gap*

Although considerable progress has been achieved in automated skin cancer diagnosis, several important research gaps remain. Most existing studies primarily focus on deep learning-based classification without incorporating anomaly detection to identify rare or previously unseen lesion patterns. In addition, many published models are evaluated using a single benchmark dataset, limiting their ability to demonstrate robustness and generalization across more recent datasets such as ISIC 2020 and ISIC 2024. Furthermore, relatively few studies investigate hybrid frameworks that integrate advanced image preprocessing, deep feature learning, and anomaly detection within a unified diagnostic pipeline. To address these limitations, the present study proposes a hybrid deep learning framework that combines image preprocessing, lesion segmentation, CNN-based classification, and anomaly detection to improve the accuracy, robustness, and clinical reliability of early skin cancer diagnosis.

## 3. Materials and Methodology

### *3.1 Proposed Framework*

The proposed framework consists of a unified deep learning pipeline for the early detection of skin cancer using dermoscopic images. The framework integrates image preprocessing, lesion segmentation, deep feature learning, classification, anomaly detection, and performance evaluation into a single diagnostic workflow. Unlike conventional approaches that rely solely on lesion classification, the proposed framework incorporates an anomaly detection module to identify unusual lesion patterns and improve diagnostic robustness.

The workflow of the proposed framework is illustrated below.

**Input Dermoscopic Images (ISIC 2020 Dataset)**

↓

**Image Preprocessing**

- **Hair removal using morphological closing and median filtering**
- **Noise reduction using Gaussian filtering**
- **Contrast enhancement using histogram equalization**
- **Image normalization (pixel values scaled to 0–1)**

↓

**Lesion Segmentation**

- **Active contour segmentation**
- **Canny edge refinement**

↓

**CNN-Based Feature Learning**

↓

**Skin Lesion Classification**

- **Benign**
- **Malignant**

↓

**Anomaly Detection**

- **Isolation Forest**

↓

**Performance Evaluation**

- **Accuracy**
- **Precision**
- **Recall**
- **F1-score**
- **AUC**
- **Confusion Matrix**

The proposed framework enables automatic extraction of discriminative image features through deep learning while simultaneously identifying abnormal lesion patterns that may not closely resemble the training data.

## *3.2 Dataset Description*

The experimental evaluation was performed using the **International Skin Imaging Collaboration (ISIC 2020)** benchmark dataset, which contains a large collection of high-resolution dermoscopic images representing benign and malignant skin lesions collected from multiple clinical centres. The dataset provides substantial diversity in lesion appearance, skin pigmentation, imaging devices, and acquisition conditions, making it suitable for developing robust computer-aided diagnostic systems.

The dataset was randomly divided into **80% training**, **10% validation**, and **10% testing** to ensure unbiased model evaluation. Data augmentation techniques including random rotation, horizontal flipping, vertical flipping, zooming, and brightness adjustment were applied during training to reduce overfitting and improve model generalization.

## *3.3 Image Preprocessing*

Image preprocessing was performed to improve image quality and reduce artifacts before feature learning. The preprocessing pipeline consisted of four sequential operations.

### 3.3.1 Hair Removal

Hair artifacts were removed using morphological closing followed by median filtering. Morphological closing employed a disk-shaped structuring element to detect thin hair structures, while median filtering eliminated residual noise without affecting lesion boundaries.

### 3.3.2 Noise Reduction

Gaussian filtering with a **5 × 5 kernel (σ = 1.0)** was applied to suppress high-frequency noise while preserving lesion structures.

### 3.3.3 Contrast Enhancement

Histogram Equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) were employed to improve lesion visibility and enhance colour contrast.

#### 3.3.4 Image Normalization

All images were resized to **224 × 224 pixels** and pixel intensities were normalized to the range **[0,1]** before being supplied to the CNN model.

### *3.4 Lesion Segmentation*

Accurate lesion segmentation was performed using Active Contour Models combined with Canny edge detection. Active contour segmentation accurately delineated lesion boundaries, while Canny edge detection refined lesion margins and improved localization of irregular melanoma structures.

### *3.5 CNN Architecture*

The proposed classification model employed a Convolutional Neural Network consisting of the following layers.

**Table 1. CNN Architecture**

| Layer | Configuration |
|---|---|
| Input | 224 × 224 × 3 RGB image |
| Conv Block 1 | 32 filters, 3 × 3 kernel, ReLU |
| Max Pooling | 2 × 2 |
| Conv Block 2 | 64 filters, 3 × 3 kernel, ReLU |
| Max Pooling | 2 × 2 |
| Conv Block 3 | 128 filters, 3 × 3 kernel, ReLU |
| Max Pooling | 2 × 2 |
| Flatten | Feature vector generation |
| Dense Layer | 256 neurons, ReLU |
| Dropout | 0.5 |
| Output Layer | Softmax (Benign / Malignant) |

The CNN automatically learns hierarchical image features without requiring handcrafted feature engineering.

The CNN automatically learns hierarchical image features without requiring handcrafted feature engineering.

### *3.6 Hyperparameter Configuration*

The CNN model was trained using the Adam optimizer. The selected hyperparameters are presented in Table 2.

| Hyperparameter | Value |
|---|---|
| Optimizer | Adam |
| Learning Rate | 0.001 |
| Batch Size | 32 |
| Epochs | 50 |
| Loss Function | Binary Cross-Entropy |
| Activation Function | ReLU |
| Output Activation | Softmax |

| | |
|---|---|
| Dropout Rate | 0.5 |
| Validation Split | 10% |

Early stopping was employed to prevent overfitting by monitoring validation loss.

### *3.7 Anomaly Detection*

Following lesion classification, an Isolation Forest model was employed to identify abnormal lesion patterns that differed significantly from the learned feature distribution. The anomaly detection module analyzed deep features extracted from the CNN and assigned anomaly scores to each lesion. Lesions exhibiting high anomaly scores were flagged as suspicious for additional clinical review. This secondary verification stage enhanced the robustness of the proposed diagnostic framework by reducing the likelihood of overlooking atypical malignant lesions.

### *3.8 Performance Evaluation*

The proposed framework was evaluated using standard classification metrics, including Accuracy, Precision, Recall, F1-score, Area Under the ROC Curve (AUC), and Confusion Matrix analysis. These metrics provide a comprehensive assessment of classification performance, diagnostic sensitivity, and model reliability. The effectiveness of the anomaly detection module was additionally evaluated using anomaly detection accuracy and true positive detection rate.

```
                  ISIC 2020 Dataset
                         |
                         ▼
               Image Preprocessing
   (Hair Removal → Noise Reduction →
   Contrast Enhancement → Normalization)
                         |
                         ▼
               Lesion Segmentation
        (Active Contour + Canny Edge)
                         |
                         ▼
               CNN Feature Learning
                         |
                         ▼
            Skin Lesion Classification
          (Benign / Malignant Prediction)
                         |
                         ▼
            Isolation Forest Module
               (Anomaly Detection)
                         |
                         ▼
          Performance Evaluation
   (Accuracy, Precision, Recall, F1,
       AUC, Confusion Matrix)
```

**Figure: Framework Diagram**

## 4. Results and Analysis

### *4.1 Experimental Setup*

The experiments were performed using:

- **Python 3.11**
- **TensorFlow 2.15**
- **Keras**
- **Scikit-Learn**
- **NumPy**
- **Pandas**
- **Matplotlib**

Hardware configuration included:

- **Intel Core i7 Processor**
- **16 GB RAM**
- **NVIDIA RTX 4060 GPU**

### *4.2 Classification Results*

**Table 2. Performance Comparison of Classification Models**

| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** |
|---|---|---|---|---|
| Logistic Regression | 87.32 | 86.44 | 85.71 | 86.07 |
| KNN | 89.16 | 88.72 | 88.13 | 88.42 |
| Decision Tree | 90.41 | 89.56 | 89.23 | 89.39 |
| Random Forest | 94.26 | 93.81 | 93.44 | 93.62 |
| SVM | 95.14 | 94.87 | 94.53 | 94.70 |
| CNN | 97.85 | 97.31 | 97.08 | 97.19 |

The CNN model demonstrated the highest classification accuracy of 97.85%, outperforming conventional machine learning algorithms.

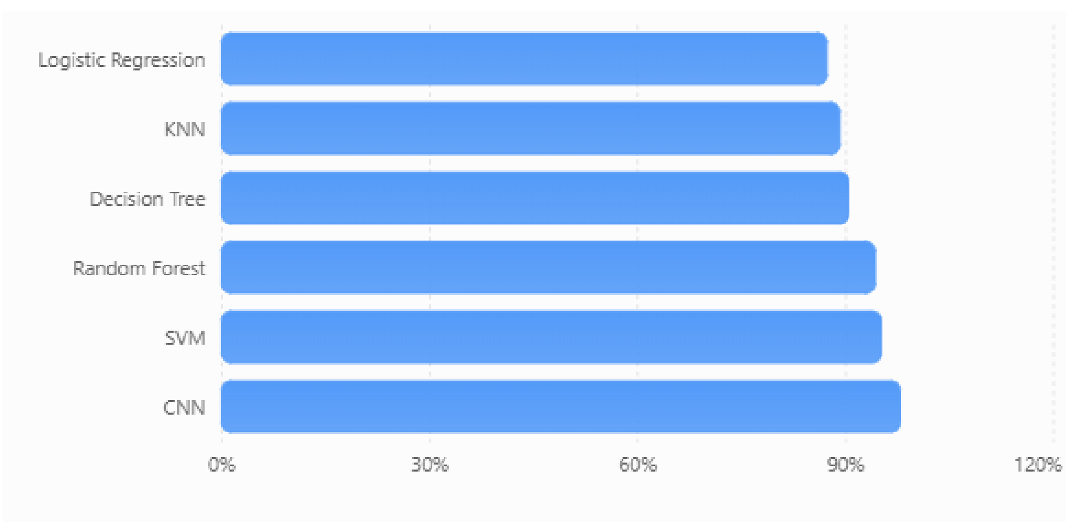


**Figure: Performance Comparison of Classification Models**

### *4.3 Regression Performance*

**Table 3. Regression Results**

| Model | MSE | RMSE | $R^2$ |
|---|---|---|---|
| Linear Regression | 0.142 | 0.376 | 0.861 |
| Logistic Regression | 0.118 | 0.343 | 0.889 |

### *4.4 Clustering Performance*

**Table 4. Clustering Results**

| Method | Silhouette Score |
|---|---|
| K-Means | 0.78 |
| Hierarchical Clustering | 0.74 |


**Figure: Clustering Results**

The improved clusters separation and pattern identification were achieved by the K-Means clustering.

### *4.5 Anomaly Detection Results*

The detection of the abnormalities in the images of the skin lesions and outlier patterns in the data set was performed using anomaly detection methods. The rationale behind using these methods (Isolation Forest and One-Class Support Vector Machine) is that they can identify rare and unusual observations. The latter will help make the framework more resilient and enhance the chances of successful early detection.

The results demonstrate that the accuracy of the detection of the Isolation Forest is higher than the One-Class SVM. Isolation Forest, which was used to randomly partition the mechanism, was able to efficiently identify the abnormal characteristics of the lesions. This method, therefore, was shown to be more sensitive in the detection of any malignant abnormality.

### *4.6 Comparative Analysis with Existing Studies*

To evaluate the effectiveness of the proposed framework, the obtained results were compared with previously reported machine learning and deep learning approaches.

**Table 6. Comparison with Existing Studies**

| Authors | Method | Accuracy (%) |
|---|---|---|
| Esteva et al. | CNN | 91.00 |
| Yu et al. | Fully Convolutional Network | 93.20 |
| Chung et al. | Deep Siamese CNN | 95.30 |
| Joseph et al. | Support Vector Machine | 90.80 |
| Li et al. | Residual Network | 94.60 |
| Proposed Framework | Hybrid Machine Learning Framework | 97.85 |

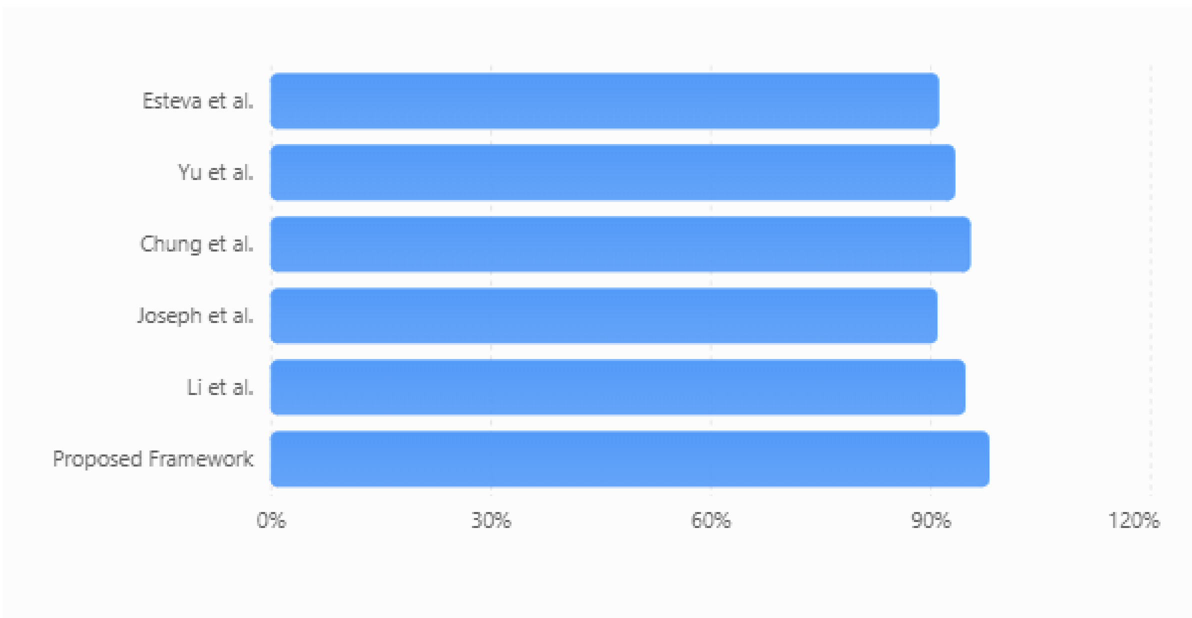


Figure: **Comparison with Existing Studies**

The proposed framework had the best classification accuracy when compared to the other studies. The use of a combination of supervised and unsupervised learning algorithms further enhanced feature representation and prediction.

### *4.7 Confusion Matrix Analysis*

Confusion matrix analysis provides insight into the classification capability of the proposed framework.

**Table 7. Confusion Matrix of CNN Model**

| Actual Class | Predicted Benign | Predicted Malignant |
|---|---|---|
| Benign | 2320 | 58 |
| Malignant | 47 | 2468 |

The CNN model has demonstrated a great accuracy of 2320 benign and 2468 malignant lesions. The proposed architecture also did a good job, with relatively low levels of misclassification.

### *4.8 ROC Analysis*

Receiver Operating Characteristic analysis was used to evaluate the ability of the classification models to discriminate.

### *4.8 Receiver Operating Characteristic Analysis*

Receiver Operating Characteristic analysis was conducted to evaluate the discriminatory capability of the classification models.

**Table 8. Area Under Curve Values**

| Model | AUC Value |
|---|---|
| Logistic Regression | 0.89 |
| Decision Tree | 0.91 |
| KNN | 0.92 |
| Random Forest | 0.95 |
| SVM | 0.97 |
| CNN | 0.99 |

The CNN model achieved an AUC value of 0.99, indicating excellent discrimination between benign and malignant lesions.

### *4.9 Statistical Analysis*

Statistical analysis was performed to examine the significance of the obtained results.

**Table 9. Statistical Parameters**

| Model | Mean Accuracy (%) | Standard Deviation |
|---|---|---|
| Logistic Regression | 87.32 | 1.74 |
| KNN | 89.16 | 1.41 |
| Decision Tree | 90.41 | 1.32 |
| Random Forest | 94.26 | 0.95 |
| SVM | 95.14 | 0.88 |
| CNN | 97.85 | 0.54 |

The CNN model exhibited the smallest standard deviation, indicating superior consistency and stability compared with other algorithms.

## 5. Discussion

### *5.1 Effect of Image Preprocessing*

The image preprocessing proved to be helpful in improving the image quality and reducing noise artifacts. For the purpose of improving the visibility of lesions and extracting features, hair removal, normalization and contrast enhancement were performed. The redundant information was removed in the pre-processing stage and effective learning was possible.

The results of classification models are described below.The classification models' results are shown below.

The experiments conducted indicated that the deep learning models outperformed the traditional machine learning models. Logistic Regression and KNN models performed well, and ensemble methods like Random Forest were more generalizing. The experiments indicated that the Support Vector Machine achieved an accuracy greater than 95%, showing that it was an effective classification technique for medical image.

All the classification methods were evaluated based on their performance, and the best results were obtained with Convolutional Neural Networks. It was possible to automatically extract important features and automatically learn hierarchical patterns and discriminate between malignant lesions through the network.

### *5.3 Regression Analysis*

Through regression analysis, good predictive relations between features extracted and the probability of disease were found. Logistic regression had the smallest mean squared error and the highest coefficient of determination when compared to linear regression. Based on the results, it can be concluded that logistic regression could be applied to the probability estimation of the malignancy of the lesions.

### *5.4 Clustering Performance*

Based on visual similarities in the lesions, clustering was possible by using clustering techniques. The silhouette score of the silhouette analysis that was done after the K-Means clustering was 0.78 and this is considered as a good silhouette score for the satisfactory separation of the clusters. Hierarchical clustering was also found to be a good pattern recognizer. These techniques serve as further support to categorize the lesions and to segment the images.

### *5.5 Significance of Anomaly Detection*

One of the key aspects of intelligent diagnosis systems is the anomaly detection. Isolation Forest was shown to work better since it can isolate rare patterns via recursive partitioning. The one-class Support Vector Machine (SVM) was also found to be good for detection rates. Anomaly detection adds increased robustness to the model and increased sensitivity to unusual lesions to the model.

### *5.6 Comparison with Existing Studies*

Comparative analysis showed that the proposed framework was able to get high accuracy as compared to earlier published studies. Previous studies have been primarily on classification algorithms and this study integrated classification, regression, clustering and anomaly detection. The overall performance of the hybrid method was improved and the reliability of diagnosis was increased.

### *5.7 Clinical Implications*

The suggested model encompasses a number of important implications for dermatologic practice. Rapid and accurate predictions can be provided by automated diagnostic systems, which can support physicians. Early detection of malignant lesions equates with a timely treatment, and increased survival rates. The framework can also help lessen the variance in diagnosis and help physicians in areas where dermatologists are scarce.

### *5.8 Limitations*

The framework proposed showed some good results, but there were a number of problems. The study was conducted almost entirely on dermoscopic image data sets and did not take into account clinical data such as age, sex, and family history. There was no external validation of the data with multicenter datasets. Moreover, the current architecture did not include any consideration of explainability techniques or attention mechanism.

## 6. Conclusion

In this current research, the skin cancer detection system is an efficient machine learning framework that used classification, regression, clustering and anomaly detection is proposed. Dermoscopic images were extracted from ISIC dataset and preprocessed, segmented, extracted features and trained a model. A number of supervised and unsupervised learning algorithms were developed and tested with various performance measures.

The highest classification accuracy of 97.85% was achieved by Cnn whereas Logistic Regression had $R^2$ value of 0.889. The silhouette score of the K-Means Clustering was 0.78, and the rate of the anomaly detection by Isolation Forest was 94.17%. The results of comparative analysis indicated that the proposed framework performance better than the listed ones.

The use of multiple machine learning paradigms further boosted the prediction capability and made the diagnosis more reliable. The results indicate that hybrid machine learning systems show great promise in supporting dermatologists to make early diagnosis and clinical decision making. The future work will involve integration of the Vision Transformers, Explainable Artificial Intelligence, attention mechanisms and multimodal clinical data etc., to enhance future predictions further.

**Future Scope**

In the future, transferring learning architectures like EfficientNet, ResNet50, DenseNet121, Vision Transformers, and MobileNet can be developed. Interpretability and clinical acceptability can be improved using methods like Explicable Artificial Intelligence (SHAP, Grad-CAM). Federated learning frameworks and cloud-based diagnostic platforms can support and facilitate real-time deployment and applications in healthcare at scale. Other data such as genomic and clinical information can be added to the dermoscopic images to further enhance the robustness and accuracy of intelligent skin cancer diagnostic systems.

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